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Simulating agricultural land-use adaptation decisions to climate change: An empirical agent-based modelling in northern Ghana

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ABSTRACT

In West Africa, the majority of regional climate projections for the region predict that the study area will become warmer and that precipitation patterns will be more erratic. The aim of this article is to examine local agricultural adaptation to climate change and variability in a semi-arid area of the Upper East Region of Ghana. This is performed by integrating the two-step decision making sub-models, Perception-of-Climate-Change and Adaptation-Choice-Strategies, to the Land Use Dynamic Simulator (LUDAS). The simulation results suggest that the land-use choices in the study area reflect a tendency towards increasing subsistence farming in an area where there has been a gradual trend away from traditional land uses such as cereal production to the cultivation of groundnut, rice, maize and soybean. Groundnut monoculture production has emerged locally as coping measure for dealing with increased climatic variability. In terms of livelihood strategy, there is an increasing contribution of rice and groundnut to household gross incomes. The predicted pattern of changes in gross household income under a scenario in which climate change is perceived by local farmers explicitly revealed the contribution of adaptation options to household livelihood strategy.

1. Introduction

Analyses of climate change and agricultural land use require a complex systems approach in which both human and environmental dynamics are studied over range of spatial and temporal scales. This approach can provide the information needed to understand inter-linkages among environmental and social problems, but it is only possible by integrating multidisciplinary research methods with dedicated disciplinary research on individual processes and mechanisms (Carpenter et al., 2009; Huber et al., 2013). One of the operationalised tools for this approach is the agent-based model (ABM).

In the recent years there has been broader application of this tool, especially with respect to land-use/cover change (LUCC) where ABM have proven to be suitable tools for representing complex spatial interactions under heterogeneous conditions and for modelling decentralized, autonomous decision making (Parker et al., 2003; Bousquet and Le Page, 2004; Schreinemachers and Berger, 2011; Schouten, 2013; Latynskiy, 2014; Villamor et al., 2014). A growing number of ABM have been built for evaluating individual farm decision making in terms of agricultural land-use systems (Parker et al., 2003), especially in the simulation of adaptation to climate change (Schreinemachers and Berger, 2011, Troost et al., 2012, Badmos et al., 2015; Christian Troost and Berger, 2015, Christian Troost, 2014). In west African context, number of research implementing ABM were developed including; SimSahel model for investigating impacts of development interventions on the Nigerien population villages (Saqalli et al., 2013a), and detecting social organisation change in Western villages of Niger (Saqalli et al., 2010; Saqalli et al., 2013b); and CaTMAS model for analyzing carbon dynamics of farming systems and sustainability of farming system in Burkina Faso (Belem et al., 2011). In the Upper East Region of Ghana LUDAS model was implemented for simulating the impact of policy interventions on land-use/cover patterns and soil loss from agro-ecosystems (Schindler, 2009; Badmos et al., 2014, 2015). Results of previous studies suggest that in order to improve estimates of climate change impacts on agricultural land uses and contribute more efficiently to adaptation research (Balbi and Giupponi, 2009; Matthews et al., 2007; Wijk et al., 2012), there is a need to better understand how farmers perceive local climate conditions and respond over both the

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short and long-term to various climate change scenarios, including the magnitude and frequency of extreme conditions (Smit et al., 1996). The use of ABM for the operationalisation of adaptive decision making about agricultural land use based on farmer perceptions of climate change and variability could help avoid misdirected adaptation efforts by isolating planned adaptation from a large number of traditional autonomous adaptation practices (Pentjuss et al., 2011; Badmos et al., 2014; Troost, 2014; Troost and Berger, 2015). The environmental specificity of agricultural adaptation options implies that most climate change adaptation options are unlikely to be undertaken independently of related risk-management initiatives. Risk management research findings, however, recognise that agricultural decisions involve both risk assessment and the determination of specific actions that can be taken to reduce, transfer or mitigate risk (Smit and Skinner, 2002).

Perceptions and decision making for predicting future land-use changes under climate change scenarios are either viewed as lacking in most land-use modelling exercises (Rounsevell et al., 2012; Verburg et al., 2016), or as rarely being directly linked to actual practices and behaviours (Meyfroidt, 2013). For this reason, we focused this research on: (1) the exploration of possible changes in dominant agricultural land uses, and (2) the implications of farmer decisions about agricultural land-use adaptation to climate change and variability in the specific context of a semi-arid region in Ghana. We adapted the framework of Land Use Dynamic Simulator (LUDAS) (Le et al., 2008). The ODD protocol (Grimm et al., 2006, 2010) of LUDAS model is explicitly described in Le et al. (2010) and Villamor et al. (2014), whereas the ODD + D protocol is described in (Villamor and Van Noordwijk, 2016). The LUDAS approach was adapted and implemented as GH-LUDAS in the Upper East Region of Ghana (Schindler, 2009; Badmos et al., 2015) and as LB-LUDAS for capturing the gendered decision making in Sumatra, Indonesia (Villamor and Van Noordwijk, 2016). In this study, we integrated into the LUDAS framework the two-step decision-making sub-model as a modification or add-on module and described using the Overview, Design, Detail plus Decision-making (ODD + D) protocol (Müller et al., 2013). We specifically focused on integrating climate change perceptions into decision-making routines. This included a research question regarding how farmers perceive risks associated with climate change (Amadou et al., 2015) and the key question about what type of stimuli agricultural land-use changes are adapting to.

2. Methodology

2.1. Study area description

The study area is located in the Atankwidi catchment in the Upper East Region (UER) of Ghana between the districts of Navrongo and Bolgatanga (Fig. 1). The study area coordinates are between 10°50′41″—11°00′35″ N latitude, and 1°03′47″—0°53′02″ W longitude. Within the catchment, the study area focused on 192 km^2 populated by four villages: Sumbrungu, Sirigu, Kandiga and Yuwa (Amadou et al., 2015). Agriculture is the main economic activity in the area. Small-scale farm households typically engage in activities such as the production of artisanal goods, trading, wood cutting and livestock production, which constitute the main sources of cash income. Most of the available land area is dedicated to small-scale agriculture during the rainy season (May–October). The area is covered by scattered household compounds that are usually surrounded by mixed crop production systems of cereals (*Sorghum bicolor* and *Pennisetum spp*), groundnut (*Arachis hypogaea*) and rice (*Oryza sativa*). There are a limited number of uncultivated patches scattered among the crop production areas that serve as grazing areas for local livestock. From the 2012 land-cover map of the area (Gerald et al., 2014), eight land-use types were classified (Fig. 2). The proportions of these land-types are reported in Table 1.

The study area is located in one of the poorest regions of Ghana where research on policy intervention impacts on local socio-economic and agro-ecological conditions is of considerable importance, especially for supporting sustainable local livelihoods.

The study area is characterised by clear seasonal changes between the dry and rainy seasons (Laube, 2005). Rainfall is marginal from November to April, with a slightly increased likelihood of rain in April, followed by almost all annual precipitation occurring between May and October. The mean precipitation from 1970 to 2010 of the closest weather station to the study area (Navrongo) is 989.57 mm. Temperatures are considerably higher than in the rest of the country, with mean monthly temperatures ranging between 18 °C and 38 °C (Martin, 2006).

The uni-modal annual precipitation pattern of the study area limits agricultural capacity and thereby the labour potential locally, as most residents are only fully engaged in agricultural labour during the brief wet season and remain without work for the rest of the year (Yaro 2000, cited in Schindler, 2009). For this reason, seasonal migration occurs from October to May (Saqalli et al., 2013a) when young adults go down to urban areas (Tamale, Kumasi, Accra, etc.) to find jobs (Laube et al., 2012).

2.2. Data collection and analysis

A total of 186 households distributed among the four villages in the study area were randomly selected and surveyed. The survey sample composition was 15% female-headed households and 85% male-headed households. Most household heads ranged ages 30 to 76. Household socio-economic data were collected using a semi-structured questionnaire during a survey conducted between January and April 2013. Three main components of agricultural land-use systems in the study area were explored through the questionnaire: (1) farming systems, (2) farmer perceptions of climate change and variability, and (3) climate change adaptation strategies. We applied Principal Component and K-means cluster analyses to derive three household agent groups. The descriptive statistics of these agent groups and corresponding livelihood indicators (variables) are summarised in Table 2. Specific agent behaviour with respect to the land use of each agent group was determined from a multinomial logistic regression (m-logit) analysis. The m-logit analysis was used to assess the choice of adaptation options and perceptions about climate change and variability were assessed based on the binary logistic regression, which in turn served as the basis for the two-step decision making sub-models (see Section 2.3.3).

2.3. Sirigu-Sumbrungu-Kandiga-Yuwa (SKY)-LUDAS: model description

The SKY-LUDAS model was developed to explicitly integrate two-step decision making used to assess the implications of climate risk perception with respect to adaptation decisions (Amadou, 2015). The land-use types (e.g., mixed cereal, groundnut, or rice production systems and pastures) generated by the land-use/cover classification of the study area (Gerald et al., 2014) and key livelihood indicators (e.g., gross income, income contributions of each land-use type, and household size of each household agent group) were considered during the model simulation. Each time step was equal to one production year. Five simulation runs were performed to compute the mean and the standard error values of each indicator.

2.3.1. Overview

2.3.1.1. Purpose. The SKY-LUDAS model is based on the previous versions of LUDAS, which were designed to: (1) support land-use decisions in the forest margins of Vietnam in consideration of different land-use policy interventions (Le et al., 2010); (2) explore the impact of policy interventions on future land-use/cover patterns and income indicators in the Upper East Region of Ghana (Schindler, 2009); and (3) explore the potential trade-offs and synergies of policy interventions on the goods and services along temporal and spatial dimensions in Indonesia (Villamor et al., 2014). SKY-LUDAS was developed for this study to explore the complex dynamics of agro-ecological systems based on how household farming systems perform

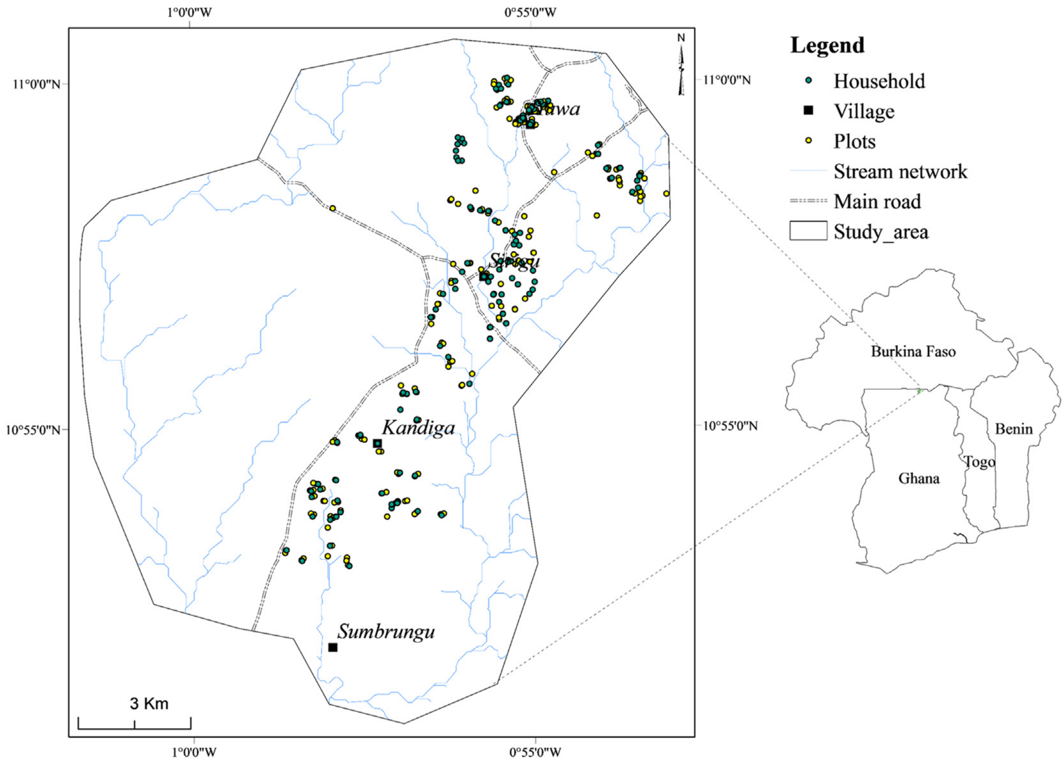

Fig. 1. Map of the study area in the Atankwidi catchment, Upper East Region, Ghana.

under climate change and variability scenarios in the study area. In addition, this model was designed to examine the relationship between population growth (i.e., household agent patterns), agricultural land-use patterns, and farmer adaptations to climate change and variability.

2.3.1.2. Agents, state variables and scales. There are two types of agents in the model: human and landscape. Human agents are represented by the individual farm households. The state variables of human agents are represented by several livelihood indicators, including; social identity, human resources, land resources, financial resources, physical capital, and policy access. The human agents are spatially explicit in the model in terms of household location. Landscape agents are represented by individual congruent land patches with a resolution of 30 m corresponding to the GIS-raster layer pixel resolution for biophysical spatial variables (e.g., land cover). The following variables are related to landscape agents: spatial proximity (e.g., distance from a house to the main river); landscape vision, which is a sphere of influence for each household agent (Le et al., 2008). The policy factors (farm input

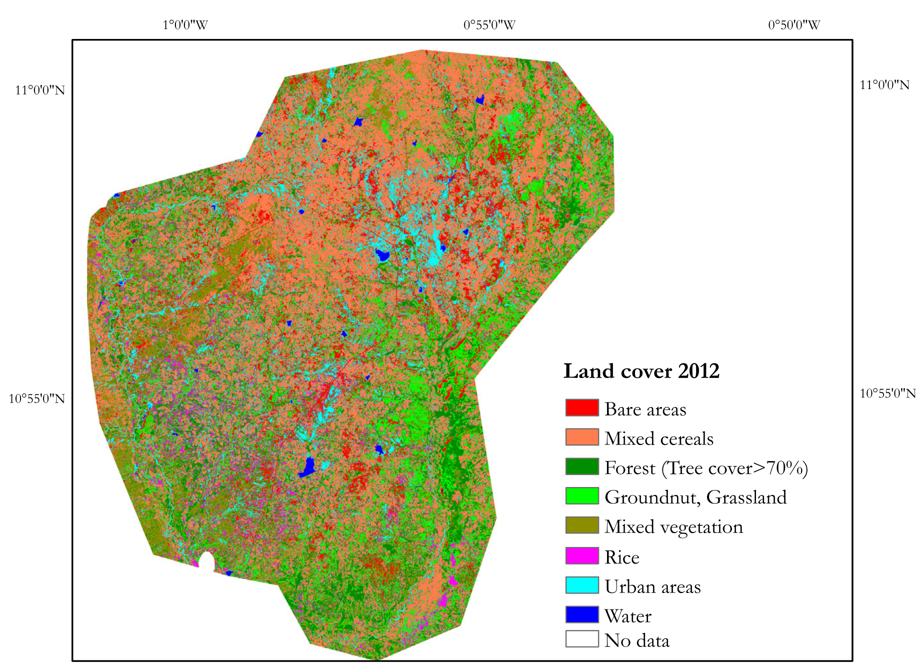

Fig. 2. Land-use land-cover types of the study area in 2012.

Table 1
Land cover surface in the study area (2012).

Land-use/cover	Description	Surface (ha)	Percentage (%)
Mixed Cereals	Cropland where millet, sorghum and maize are the main crops in the cropping system	7569.45	39.4
Rice	Cropland referring to rice in mono-cropping	857.07	4.5
Groundnut and grass	Cropland of groundnut and Grassland	2813.67	14.6
Mixed vegetation	Combinations of shrub, trees and grass	1538.64	8.0
Forest/trees	Areas with a tree cover greater than 70% and single trees on farm plots	2873.79	14.9
Bare lands	Bare areas and laterite roads	1859.31	9.7
Urban	Houses, settlements, rock outcrops, tarred roads and other artificial surfaces	1608.21	8.4
Water	Small reservoirs and rivers	79.74	0.4
No Data	Areas covered by clouds	23.4	0.1

Table 2
Descriptive statistics of select key categorising variables for each of the household agent groups.

Variable	Agent group	Household	Mean	Std	Error
Size	I	78	5.86	2.07	0.23
	II	55	5.05	2.44	0.33
	III	53	8.66	3.71	0.51
Dependency ratio	I	78	1.10	1.05	0.12
	II	55	0.36	0.31	0.04
	III	53	0.55	0.49	0.07
Labour (man-day)	I	78	141.74	66.43	7.52
	II	55	106.95	65.00	8.76
	III	53	279.73	119.67	16.44
Gross income per capita (Ghanaian Cedis)	I	78	418.39	318.60	36.07
	II	55	278.93	197.28	26.60
	III	53	554.50	310.31	42.62
Total lands	I	78	1.96	1.20	0.14
	II	55	1.44	1.09	0.15
	III	53	3.27	1.52	0.21
Livestock index	I	78	4.28	7.24	0.82
	II	55	7.56	11.75	1.58
	III	53	4.26	4.34	0.60
Cattle number	I	78	0.97	1.65	0.19
	II	55	1.49	1.76	0.24
	III	53	3.30	3.23	0.44
Income groundnut (%)	I	78	53.26	19.47	2.20
	II	55	9.65	13.33	1.80
	III	53	30.45	15.62	2.14
Income rice (%)	I	78	3.86	9.90	1.12
	II	55	2.96	8.11	1.09
	III	53	21.09	18.16	2.50
Income cereals (%)	I	78	42.88	18.52	2.10
	II	55	87.39	16.40	2.21
	III	53	48.46	17.13	2.35

subsidies, weather information, and climate change mitigation efforts) are considered externally with regard to the boundary of the modelled system in order to define different scenarios and policy management options. Space was implicitly included in the model by importing a land-use map covering 192 km^2 with 30 m × 30 m cell pixel size. The land-use/cover map (Fig. 2) was generated from a remote sensing-based analysis of crop distribution in the research area from 2012 (Gerald et al., 2014). Other landscape layers (e.g., slope, upslope, humidity index) were generated from GIS-based calculations using digital elevation model (DEM) datasets of the area.

2.3.1.3. Process overview and scheduling. Each time step represents one year. The model simulates a period of 20 years. The main time loop of the simulation, called an annual production cycle, includes sequential steps that are agent-based and integrated with patch-based processes (Villamor et al., 2014). The main steps specified by SKY-LUDAS during a simulation include: (1) set-up initial state of the system, (2) update agent and patch attributes, (3) adopt behaviour parameters, (4) agricultural land use choice, (5) other sources of income, (6) update agent and patch attribute changes, (7) categorise households, (8) translate annual land-use changes, (9) create new agents, and (10) calculate crop productivity. The SKY-LUDAS model was coded using Netlogo version 5.0.3 (Wilensky, 2010). A portion of an interactive model interface, map and graphs tracking simulated data over time was showed in Fig. 3. The scheduling programme of LUDAS is described in greater detail in previous studies (Le et al., 2008; Villamor et al., 2014; Amadou, 2015).

2.3.2. Design concepts

2.3.2.1. Learning. Learning was integrated into the model to enable simulation of adaptive behaviour, since an agent should base decisions on regularly updated information (Latynskiy, 2014). The adaptive traits of each individual agent are explicitly processed primarily by land-use decisions and behavioural strategy changes. At first, agents adapt to existing socio-ecological conditions by choosing the best land use in the best location in terms of utility. Then, individual household behaviour models may change by imitating the strategy of the household group most similar to it (Le et al., 2010). In this way, individual agent decision models may change over time and context. Also, a household agent generates landscape knowledge by updating landscape visions (Villamor, 2012) to provide the basic landscape structure.

2.3.2.2. Individual sensing. For evaluating land-use choice, household agents are assumed to have perfect knowledge of landscape characteristics through landscape vision, which varies depending on the household agent category. The evaluation of adaptation strategies is then guided by the perception-of-climate-change sub-model.

2.3.2.3. Individual prediction. The model has a landscape vision module, which stores spatial information about the landscape perceived by each household agent, and a programme of instructions for generating agent behaviour under different circumstances. Accordingly, household agents only recognise spatial information for optimising spatial land-use choices on their own plots (Villamor et al., 2014).

2.3.2.4. Interaction. Household agents and their local environment are characterised by complex systems of interactions. In this regard, agents may not only interact with each other, but also with the environment, thus redefining its state. For instance, household agents transfer information (i.e., state variables) to young agents at the same location for their optimal land-use option. Interactions between household and landscape agents occur mainly through tenure relations and a perception-response loop. Tenure relations are institutional rules that regulate household access to land resources. The perception-response loop involves information flows between households and patches. The information flowing from household to patch reflects the decisions made by the household with respect to land use on the patch. The information flowing from patch to household corresponds to the perceived bio-physical state and benefits that the household can derive from the land use to inform decision making. Policy and other macro-drivers influence system behaviour by

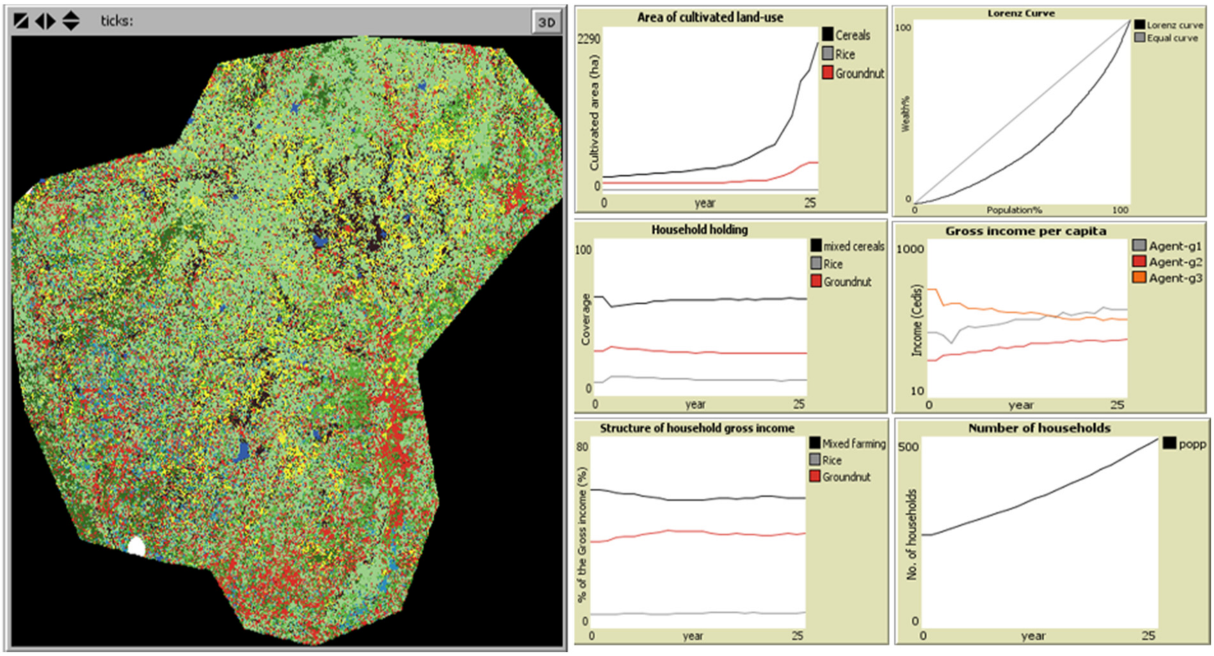

Fig. 3. Interactive model interface, map and graphs tracking simulated data over time.

modifying the functional relationships between the human and environmental systems (Le, 2005).

2.3.2.5. Collectives. Both human and landscape systems are self-organised according to a hierarchy of three organisational levels. The three organisational levels of the human system are: (1) household agents, representing the individual farm households of the study area; (2) groups of household agents, which refer to collections of household agents with a similar livelihood typology and therefore assumed to have similar land-use behaviour; and (3) the whole population representing the collection of all agents, the pattern of which is a result of emerging processes at the lower levels of the hierarchy system. The three organisational levels of the landscape system are: (1) landscape agent; (2) landscape vision; and (3) the entire landscape.

2.3.2.6. Heterogeneity. Farm household agents are heterogeneous in terms of variable states, spatial locations, and agent categorisation. They are also heterogeneous in their decision making in terms of land use decisions. Another expression of heterogeneity is the adaptation decision mechanism, which in addition to the household profile is guided by the probabilistic sub-model of farmer perceptions regarding climate variability.

2.3.2.7. Stochasticity. This model uses empirical data to establish initial household state and landscape attributes. For every subsequent time loop of the simulation, the household attribute values are approximated stochastically within the uncertainty range values of the previous time step.

2.3.3. Details

2.3.3.1. Initialisation. Data and parameters are defined, calibrated externally, and organised in text format. Data include GIS-raster and household data as well as specific parameters. The household and GIS datasets were needed to establish the initial conditions of the coupled human-landscape, while parameters specify various internal routines of the model. The model used the annual population growth rate of 2.5% as the annual population increment according to the 2010 population and housing census in Ghana (GSS, 2012).

2.3.3.2. Sub-models. There are 12 key sub-models and calculation routines integrated into the general framework of LUDAS platform (Villamor et al., 2014). Table 3 summarises the key parameters and data sources used to parameterise and calibrate some of the key sub-models. In addition to land-use choice, five ecological sub-models were considered (Table 3) due to their close relationships to biophysical conditions and population dynamics. The indicators involved in computing the agronomic sub-models are also determined by land use.

2.3.3.3. Individual decision making. Decision making is modelled at the individual household level and integrated into *decision-making routines* in simulating household-specific land-use behaviour (Le et al., 2008; Villamor and Van Noordwijk, 2016). After every time step, each agent is assigned to a group with similar values (updated household attributes). Hence within the household agent group in which the socio-economic attributes are assumed to be similar, all households also exhibit similar decision-making outcomes. In the SKY-LUDAS framework, like many other ABM, the dynamic processes are scale dependent. Especially in the field of LUCC research, the prevailing outcomes at the level of the general population are the result of interactions at lower levels. Hence, in the model the human system is hierarchically structured. Due to the reallocation of households into groups characterised by the greatest similarity at the end of each time step household agents will adapt to new behaviour parameters shared among members of this new group, which in turn will affect decision-making processes. Household decision making is utility-based, modelled by the decision-making mechanism representing choices among a discrete set of options (i.e., land-use and adaptation options) and using the utility function to estimate the ‘profit’ offered by each option. Utility values for each option are calculated by multinomial logistic analyses. The mechanism works based on the inputs from the household profile, policy-related variables, and the perceived state variables of the landscape patches for which land-use decisions are made.

Two additional procedures were added to the decision programme routine, Farmers' perception and Adaptation choice, and nested in FarmlandChoice that forms a two-step decision-making process (Fig. 4). This procedure was designed in accordance with the decision-making approach developed in LB-LUDAS in order to capture process-based

Table 3
Key parameters and sub-models integrated in the SKY-LUDAS model.

Sub-model	Parameter	Analytical framework	Data source
Land-use choice	Characteristics of farm plot user (e.g., age, education, status, income, etc.), natural land attributes (e.g., elevation, slope, soil fertility, etc.), policy related variables (extension, subsidy, etc.)	M-logit model (Greene, 2002, 2012; Train, 2009) $\Pr\left(Yi = {}^{j}/_{Xi}\right) = \frac{e^{\beta_j' X_i}}{1 + \sum_{k=1}^{J} e^{\beta_k' X_i}}$ $j = 0, 1, 2, \ldots, J, \beta_0 = 0$ where P_r is the predicted probability of choosing land use option Y_i, j represents the categories of the dependent variable Y as observed outcome of the *i-th* observation, X_i is a vector of the *i-th* observation for the explanatory variables, β_k is a vector of all regression coefficients (preference coefficients) in the *j-th* regression	Field survey (2012 – 2013): GIS analyses of the Digital Elevation Model (DEM) datasets; GIS analyses of soil map
Agricultural yields in mixed cereal production system	Labour, agrochemical inputs, organic matter inputs, livestock index, soil fertility, plot area, flow accumulation and slope gradient of the plot Early millet: 1160 kg ha^{-1} y^{-1}; Late millet: 1490 kg ha^{-1} y^{-1}; Sorghum: 1514 kg ha^{-1} y^{-1}	Production function model (Cobb and Douglas, 1928) $P_{yield} = a.\ I_{labor}{}^{\beta_1}.\ I_{chem}{}^{\beta_2}.\ I_{org}{}^{\beta_3}.\ I_{liv}{}^{\beta_4}.\ I_{soil}{}^{\beta_5}.\ I_{slp}{}^{\beta_6}.\ I_{upslp}{}^{\beta_7}$ where P_{yield} is the agronomic yield, *a* is a constant, I_{labor} is labour input, I_{chem} is the agrochemical input, I_{org} is organic matter input, I_{livest} is a livestock index, P_{soil} is patch soil fertility, P_{area} is patch area, P_{slope} is patch slope, $P_{upslope}$ is patch upslope, and β_1 to β_8 represent yield elasticity for the corresponding parameters	Field survey (2012–2013): GIS analyses of the DEM datasets; GIS soil map analyses; field measurements using the GPS area calculation function
Agricultural yields in groundnut production system	Labour, livestock index, soil fertility, plot area, flow accumulation and slope gradient of the plot Groundnut: 1086 kg ha^{-1} y^{-1}		
Agricultural yields in rice production system	Labour, agrochemical inputs, livestock index, soil fertility, plot area, flow accumulation and slope gradient of the plot Rice: 1257 kg ha^{-1} y^{-1}		
Perception of climate change	Characteristics of farm plot user (e.g., age, gender, etc.); Local agro-ecological setting of the household (e.g., elevation, slope, etc.); Policy related variables (e.g., information on weather and climate), perception as binary outcome with a value 1 or 0	Binary logistic model (Greene, 2002, 2012; Train, 2009) $\log\left(\frac{P_i}{1 - P_i}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_{ik}$ where *i* denotes the *i*-th observation in the sample, P_i is the predicted probability of farmer perceptions coded as a dummy variable with the value of 1 when farmer has a clear perception of climate change and 0 otherwise (1 - P_i), β_0 is the intercept term, and $\beta_1 \beta_2$, and β_k are coefficients associated with explanatory variables X_1, X_2 and X_k, P_i/1-P_i represents probability values, and the coefficients in the logistic regression were estimated using the maximum likelihood estimation method	Field survey (2012–2013): GIS analyses of the DEM datasets
Land-use adaptation choice	Characteristics of farm plot user (e.g., age, education, status, income, etc.), natural land attributes (e.g., humidity index, soil fertility, etc.), policy related variables (extension, subsidy, etc.)	The analytical framework follows the multinomial logistic model (M-logit model) as stated above, where P is the predicted probability of adaptation to choose option Y_i, j represents the categories of the dependent variable Y as observed outcome for the *i-th* observation, X_i is a vector of the *i-th* observation of the explanatory variables, and β_k is a vector of all regression coefficients (preference coefficients) in the *j-th* regression. The humidity index $P_{humidity} = \ln\left(\frac{P_{upslope} \times r}{\tan P_{slope}}\right)$ where, $P_{humidity}$ is the humidity index, $P_{upslope}$ the upslope contributing area, P_{slope} the slope gradient and r is the resolution of the digital elevation model raster (30 m).	Field survey (2012–2013): GIS analyses of the DEM datasets; GIS soil map analyses

decision-making (Villamor, 2012; Villamor and Van Noordwijk, 2016). Accordingly, the Perception-of-Climate-Change and Adaptation-Choice sub-models were integrated into the LUDAS decision module, particularly within the Farmland-Choice procedure as a household agent decision-making mechanism (Le et al., 2008). The first step simulates farmers' perception of climate change while the second step simulates the choice of land-use adaptation strategies, but only if the farmer perceives the need to adapt to climate change (Fig. 4). These two-step decision-making routine developed through the decision programme as different procedures are performed by each household agent in every time step, independently of the agent's group, as specified in the following:

(1) The first step was developed based on the results of a binary logistic regression analysis (Amadou et al., 2015). The probability, $P_{\_hij\text{-}perception}$, is a binary outcome of Perception-of-Climate-Change through a dummy variable that takes a value of 1 when the farmer perceives climate change and 0 otherwise. When the value of $P_{\_hij\text{-}perception}$ is 0, the decision programme skips the adaptation procedure and proceeds to the common Farmland-Choice routine. In this case, only the baseline conditions are run for each household agent. In contrast, when the value of $P_{\_hij\text{-}perception}$ equals 1 the decision programme activates the AdaptationChoice routine to compute the probability of choosing an adaptation option (Fig. 4), on the basis that household agents who perceive climate change are engaged in a multiple choice procedure.
(2) The second step sub-module was designed based on the results of the m-logit analysis of the probability of selecting one of four adaptation choices: (i) crop-livestock integration, (ii) irrigation, (iii) maize (*Zea mays*) and soybean (*Glycine max*) farming, or (iv) 'no adaptation,' the latter having been used as the base category in the m-logit analysis. When a household chooses a particular adaptation option, then that option is executed in the Farmland-Choice routine, especially during the moving phase. This second step involves many indicators, especially labour force, to perform a particular selected option.

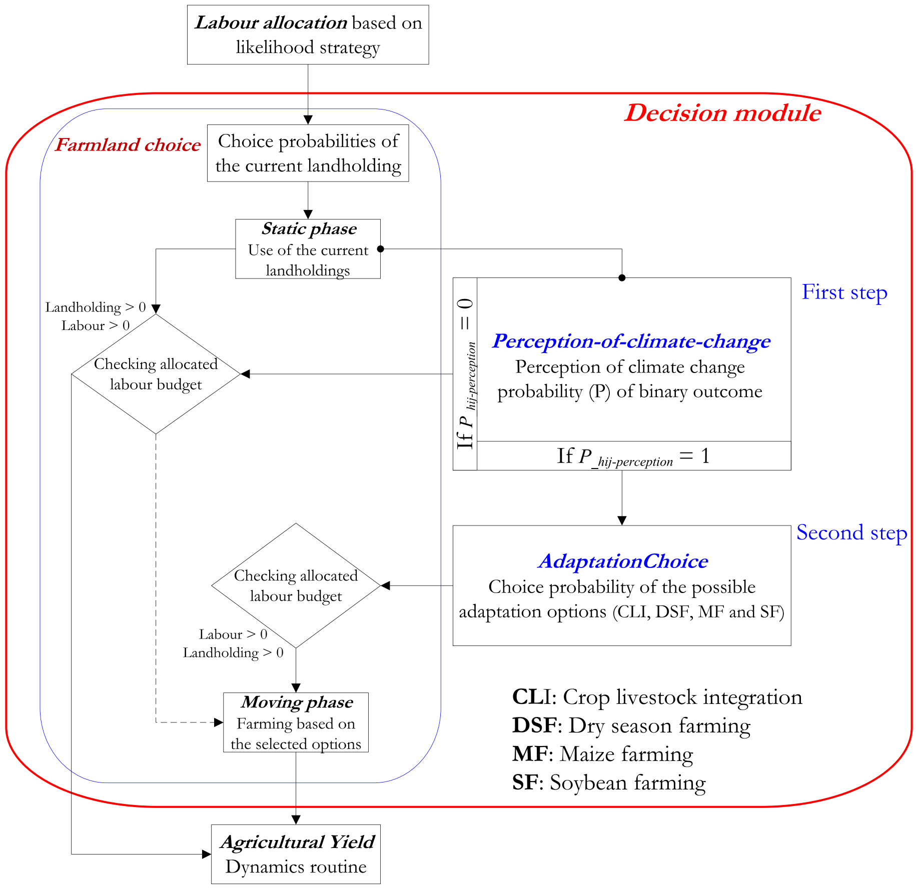

Fig. 4. Schematic representation of the two-step decision-making routine integrated into the SKY-LUDAS decision programme.

The socio-ecological interactions of the five different land-uses (crop-livestock integration, irrigation, maize farming, soybean farming, and no adaptation) selected for the simulations are as follows:

(1) Crop-livestock integration is specific to those households that own livestock, especially cattle. These households have the capacity to produce manure, the means to transport composted manure to their fields, and the means to plough such additives into the soil. As a result, they are able to enhance soil fertility, which is mostly associated with mixed and inter-cropping cereal production systems where many crops are grown on the same plot of land. In order to consider the interactions within this option for households that opt for it, variables such as livestock index, manure application and fertility management were improved stochastically using random values bounded by the correspondent standard deviations.
(2) The irrigation option regards households that engage in dry season farming as a response to climate change and variability. In the moving phase (Fig. 4) a household agent can 'open new land' for dry season farming subject to the following conditions: (1) the land-cover option should be implemented on farmland suitable for rice, and (2) the humidity index should be greater than zero in order to avoid upland rice production areas because irrigation is restricted to areas along the river. Subsequently the ecological sub-module built for landscape agents (agricultural yield) is applied to crops grown in the dry season.
(3) Maize and soybean farming were the two crops introduced in the study cite. From our household survey, 11.8% of the respondents adopted these crops in their farming practices for coping with the reduction of production due to the long-term changes in temperature and rainfall. These have been observed adaptation strategies in similar studies in the region (Dah-gbeto and Villamor, 2016). Therefore, the ecological sub-module (Agricultural yields) for these two crops was integrated in the moving phase.
(4) No adaptation occurs when an agent decides not to apply any of the available adaptation measures.

2.4. Model scenarios

We simulated the three following scenarios using the SKY-LUDAS model as described in Table 4: Business-as-usual, Perception of climate change and variability (PCC), and No perception of climate change and variability.

Adaptation of agents was assessed based on the dominant agricultural land-use patterns (i.e., mixed cereal, rice or groundnut production) simulated for each scenario and the corresponding income structure of the farm household agent groups for a 20-year period.

2.5. Model validation

We validated the model based on expert opinion (Villamor et al., 2012), especially on previous modelling efforts undertaken in the area, as well as through the use of a role-playing game (RPG) to better understand decision making regarding land-use adaptation (Suphanchaimart et al., 2005). The use of RPG with ABM is one of the methods for convergent validity (Villamor et al., 2013) following the concept of Summers and MacKay (1977) that if the results of the two completely different independent methods are in close agreement, both are said to share establishment of convergent validity. We conducted 20 RPG exercises in the four study area communities following Suphanchaimart et al. (2005) for the purpose of validating the SKY-LUDAS model. In terms of land-use distribution on the landscape, factors such as water availability and topography are considered. The

Table 4
Model scenarios.

Scenario	Description
Business-as-usual	Business-as-usual corresponds to the baseline where decision-making programme follows the empirical land-use choice model as benchmark (Le et al., 2008). Basically, existing main agricultural land-uses (mixed cereal, rice, and either monoculture and mixed-crop groundnut production systems) were simulated based on the agent's landholdings over a 20-year period, with changes to biophysical conditions based on model dynamics and population increases.
Perception of climate change and variability (PCC)	PCC scenario simulates the two-step decision-making process (Fig. 4). The values (0 or 1) representing farmer perception probabilities in the first step and the available labour budget determine the implementation of the second step, where relative probabilities for each of the adaptation options were calculated.
No perception of climate change and variability scenario (NO-PCC)	This scenario stops the routine of the first step in the PCC scenario. By doing so, no more restriction related to the Perception-of-Climate-Change in the decision programme will result. In this case only the decision programme runs the second step (*AdaptationChoice*) for all the farm household agents. Only labour budget can limit household agents in the implementation of a selected land-use adaptation option.

farmland land uses are mixed cereal, mixed groundnut, monoculture groundnut, rice, maize, soybean, bean (*Vigna unguiculata*) and Bambara bean (*Vigna subterranea*) production systems.

Groups were mixed in some places but constituted only by farmers who participated to the individual surveys. Among the players who perceived the risks associated with climate change and increasing climate variability, 12 were selected for individual RPG exercises to validate the SKY-LUDAS land-use adaptation simulations, especially the PCC scenario (see Section 3.3).

In terms of the distribution of farmlands on the landscape, the following land uses included: mixed cereal, mixed groundnut, monoculture groundnut, rice, maize, soybean, bean (*Vigna unguiculata*) and Bambara bean (*Vigna subterranea*). Factors such as water availability and topography were also considered. Each time step or round of the game represents 1 annual production cycle. Therefore, with each group, we conducted five rounds of game with regards of the following scenarios: baseline, delay in the onset of rains, early onset of rains, a 50% cost of subsidised fertilizer, and having credit available to the player. The game board representing available land is organised by a grid of 4×3 cells, each of which measures 5×5 cm, for a total of 12 patches of land on the game board.

3. Simulation results

3.1. Agricultural land-use patterns

Mixed cereal farming remained the primary land use followed by groundnut and rice production. A clear increase in the area of mixed cereal production resulted regardless of the scenarios (Fig. 5a). Rapid expansion of rice production was exhibited until year seven (Fig. 5c) at which point it became relatively constant over time. Groundnut production also increased slightly and became an important crop in the last four years (Fig. 5e). Aggregated household agents followed a similar pattern for each land-use type. This was used to examine the relationships between population dynamics and the scenario designs with respect to the different household livelihood strategies (especially in terms of the temporal pattern of land-use change and productivity). As a result, the population pattern did not appear to influence land-use changes under the different scenarios at the level of household aggregation modelled.

Among the scenarios, NO-PCC exhibited the greatest area converted to mixed cereal (Fig. 5b) and rice (Fig. 5d) production, with 1113 ha and 2 ha respectively in average change over the 20-year period. The increase of mixed cereal cultivation reflects the extensive farming system characteristics in the study area as supported by its spatial dominance under both the baseline and NO-PCC scenarios.

Under the PCC scenario household agents pursued a variety of livelihood alternatives or other adaptation options (i.e., crop-livestock integration, irrigation, maize or soybean farming). The area of mixed cereal cultivation under the PCC scenario had the lowest values (Fig. 5a) and the least land-use change (from 235 ha at year 1 to 859 ha at year 20) relative to the other scenarios (Fig. 5b). The PCC scenario exhibited the greatest increase in groundnut cultivation area (Fig. 5e), with a change of 70 ha as compared to the baseline of 57 ha (Fig. 5f) where groundnut was used as cash crop, especially in the case of monoculture systems. In contrast, rice cultivation had the lowest value under the PCC scenario (Fig. 5d), therefore, the motivation for growing rice is not related to climatic condition.

3.2. Household income structure

Mixed cereal production represented the greatest contribution to income for all household agents despite declining over time (Fig. 6a). This finding confirms the extensive and subsistence oriented behaviour prevalent in the study area. In this regard, mixed cereal represents the land-use type with the greatest percentages for household agent groups II and III, household agent group I (Table 2) exhibited an emphasis on groundnut farming in terms of income contribution to the household revenue.

For household agent group I, with a groundnut income contribution of 53%, exhibited greater diversification of agricultural land use, including both monoculture and mixed groundnut systems as well as cash crops like maize and soybean (Amadou, 2015). Even though the cultivated area of mixed cereals increased over time (Fig. 5a), this land-use type is exhibited a downward trend over time in terms of household income contribution (Fig. 6a), which suggests changes in livelihood strategy among the household agents. Household agent group II exhibited greater reliance on cereal production (87.4% income contribution) implying a livelihood strategy that emphasizes subsistence farming rather than cash crops. Group III was noticeably different with respect to rice cultivation (21% income contribution), likely due to greater availability of labour and land resources reported by members of this group (Table 2). Based on income composition household group III appears to be food sufficient.

The PCC scenario had the lowest mixed cereal income contributions, which indicates that farmers who perceive the risks associated with climate change and variability are predicted to increase cultivation of other crops. The increasing income contribution of rice and groundnut under the NO-PCC and PCC scenarios were greater than under the baseline scenario (Fig. 6c, e). The greater predicted increase in the income contribution of rice under the NO-PCC scenario suggests that farmers who perceive the risks of climate change are more likely to increase groundnut cultivation as livelihood strategy relative to rice. This may be due to the fact that rice farming is more demanding in terms of labour, water, farm inputs and care, and thus, is not a suitable diversification option for most small-scale farmers.

3.3. Role-playing game results

The results of the RPG exercises (Fig. 7) were meant to improve our understanding of the land-use decisions among members of each study area community. For all the four communities, traditional or mixed

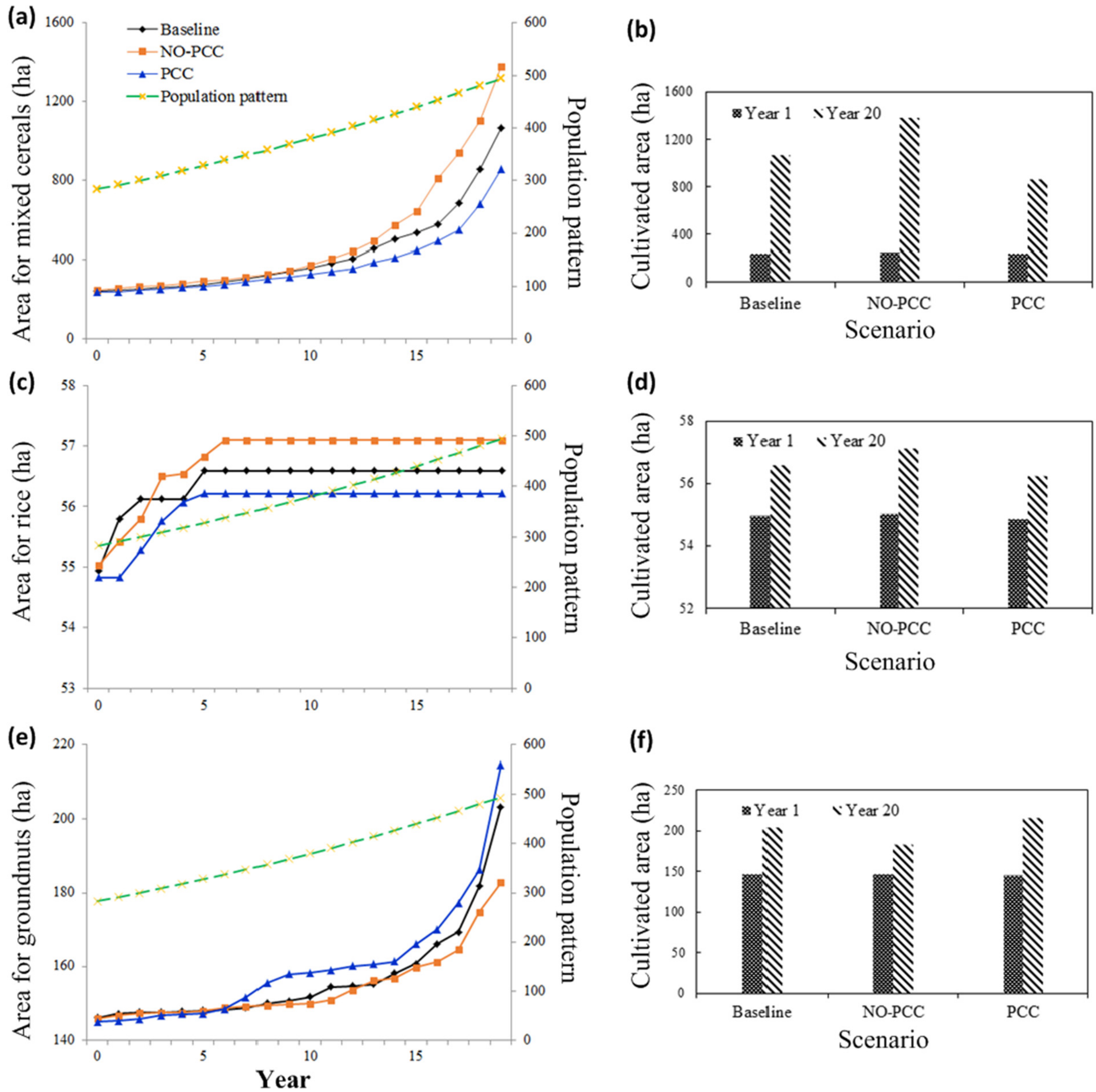

Fig. 5. Predicted changes over time in the cultivated areas of the main crops grown in the study area (e.g., mixed cereals, rice, and groundnut) under population growth and the three model scenarios. 5.a.- Mixed cereal cultivation area. 5.b.- Change in mixed cereal cultivation area. 5.c.- Rice cultivation area. 5.d.- Change in rice cultivation area. 5.e.- Groundnut cultivation area. 5.f.- Change in groundnut cultivation area.

cereals constituted the primary land-use with a mean total area of 26%, followed by rice and maize (17% each), groundnuts (15%) and soybean (7%) (Fig. 7a). Traditional cereals are staple foods and also used in funeral celebrations.

Under normal precipitation pattern conditions (baseline), groundnut is grown in mixed crop and monoculture systems (Fig. 7a). Under the delayed onset of rains scenario, farmers chose to continue to cultivate groundnut monocultures in some communities, but increased mixed crop groundnut production in areas that formerly supported monocultures (Fig. 7b). In one of the communities, the RPG exercise participants chose to discontinue the use of monoculture groundnut systems entirely. Local farmers reported a shift from the traditional groundnut variety to early maturing varieties independent of the cultivation system used to cope with drought and shorter rainy seasons, which lead to drier soils that make it difficult to harvest the groundnut. Under the early onset of rains scenario (Fig. 7c) farmers generally chose to implement the same land-use practices as they did under the baseline scenario.

The RPG exercise findings supported the SKY-LUDAS simulation results that identified groundnut monoculture systems as an agricultural land-use adaptation strategy.

4. Discussion

4.1. Land-use adaptation response

The most common response to perceived climate change included the introduction of new crops (maize and soybean), changing crop varieties, crop-livestock integration, and irrigation. Our findings are consistent with the results of a number of studies that focused on adaptation strategies among local households in the study area in response to environmental changes that threatened agricultural livelihoods (Preston and Stafford-smith, 2009; Troost et al., 2012; Iwamura et al., 2014; Kurukulasuriya and Rosenthal, 2003; Patt and Siebenhüner, 2005; Jouve, 2010). A similar study in Ghana identified diversifying crop types and changing planting schedules the prevailing

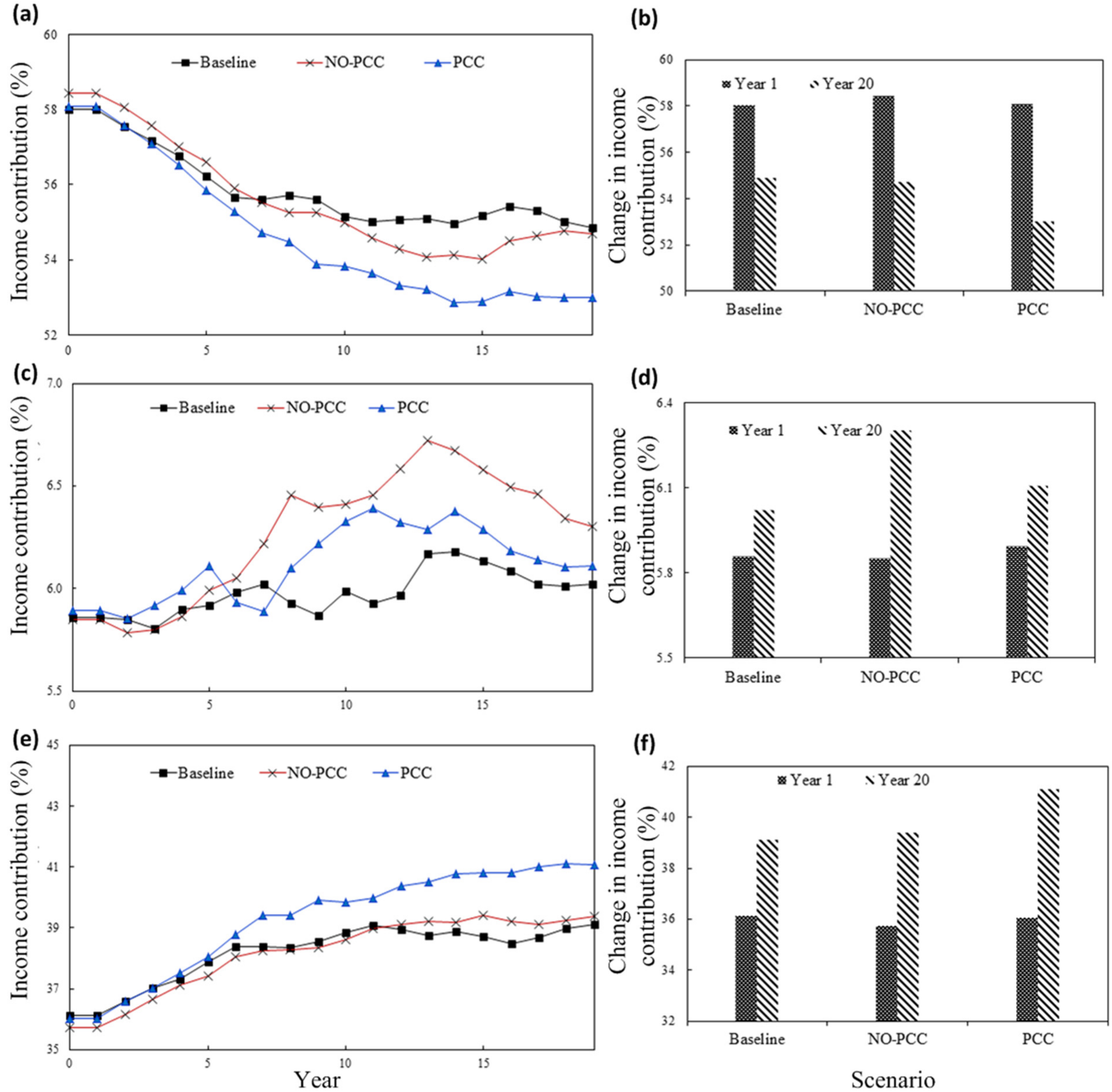

Fig. 6. Predicted changes over time in income contributions of each major crop under population growth and the three model scenarios. 6.a.- Income contribution of mixed cereals. 6.b.- Change in income contribution of mixed cereals. 6.c.- Income contribution of rice. 6.d.- Change in income contribution of rice. 6.e.- Income contribution of groundnut. 6.f.- Change in income contribution of groundnut.

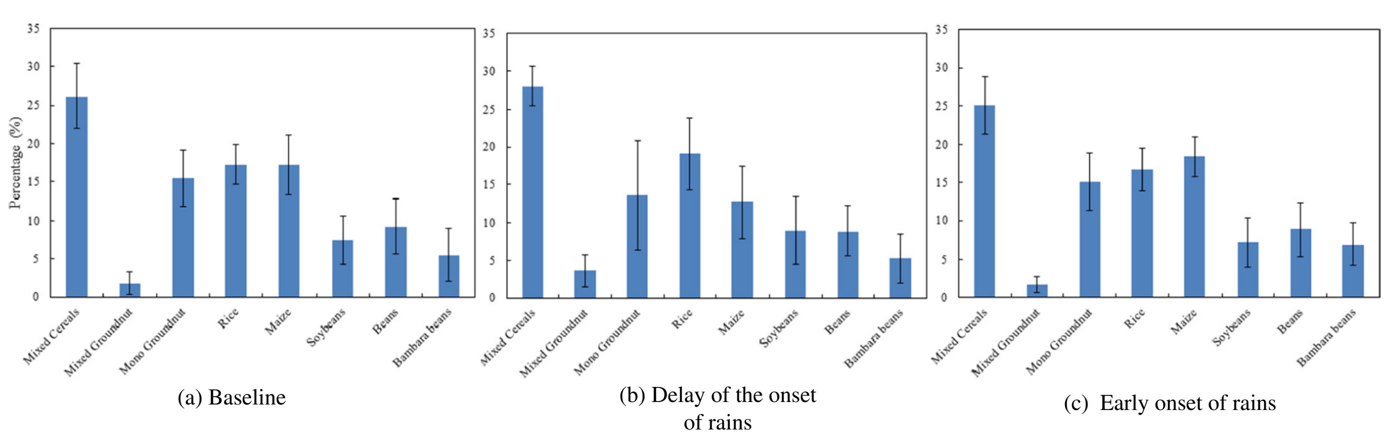

Fig. 7. Land-use patterns resulting from the RPG exercises in the study area communities under three scenarios.

adaptation strategies for coping with the effects of climate change (Badmos et al., 2014). New crops such as maize and soybeans with shorter growth cycles replaced traditional crops such as local cereals like millet or guinea corn and groundnut (Laube et al., 2012). Another study found that significant proportion of farmers (41%) appeared to have changed management practices in response to declining precipitation, with crop diversification and shifting planting dates being the most important adaptation measures (Fosu-Mensah et al., 2010). The SKY-LUDAS model revealed a gradual shift among land-use types from traditional cereal farming to greater cultivation of rice and groundnut, which was also observed over recent decades in the study area (Schindler, 2009). Our findings indicate that farmers who are well aware of climate variability were more likely to shift to groundnut farming than rice because rice farming demands more labour, water, inputs and care. A transition from traditional small-scale agriculture has been observed in many parts of the UER, Ghana where agricultural intensification has mainly occurred through the adoption of irrigation practices and new crop varieties that are considered more suitable to perceived environmental changes (Laube et al., 2012). Significant shifts have not been documented for patterns of traditional small-scale agriculture (Laube et al., 2012) as a result of increasing delay of rainy season onset despite the fact that local farmers have reported such changes since the mid-1980s (Laux and Kunstmann, 2008). Rice and groundnut cultivation have exhibited upward trends relative to mixed cereal systems in terms of overall production area. Despite the factors discussed above, when it comes to livelihood strategy and especially income structure, there was a growing contribution of rice and groundnut. One of the main reasons for this land-use change trend was that the younger generation of farmers tends to prefer cash crops such as rice and groundnut over traditional subsistence crops. This was supported by the empirical data set, which showed a much higher percentage of such crops among younger farmers (Schindler, 2009).

Many factors are expected to affect adaptation to climate risks in arid areas. The perception model of local households should be considered in agricultural adaptation research in order to determine appropriate measures for coping with climate variability (Smit et al., 1996; Maddison, 2006). However, the reality of study area is that even tough people are living as different communities in this area, when it comes to farming, a given community can have its croplands in the territory of other communities. For instance, some of farmers from *Kandiga* have to pass through *Sirigu* to access to their farmlands in *Yuwa* territory. Therefore, there is a module called *landscapevision* integrated in SKY-LUDAS model which plays a role of sphere of influence of households. After each time step, this module updates the maximum distance each household can reach for farming. Also, demography and land use change, are all considered in the simulations. Accordingly, in Fig. 5 we examined the relationships between population dynamics and the three scenarios with respect to the different household livelihood strategies. And the conclusion was that, when all household types are aggregated, land-use changes appear more related to the different scenarios than the population pattern.

The importance of understanding the effect of awareness of climate change (the PCC scenario) could also be associated with the fact that in the study area, younger farmers were more educated and therefore more interested in access to information on weather conditions, which was one of the main determinants of the *Perception-of-Climate-Change* sub-model (Amadou et al., 2015). Education is recognised as improving farmer perceptions, then it is logical to expect education to influence management practices and the agro-ecological landscape at their disposal (Ellis and Swift, 1988).

On the other hand, the adaptation decisions of farmers may not be motivated by climate change. For instance, it was found that increased income from farming was generally due to higher yields, cultivation of more valuable crops, and/or an extension of cropped area, or a combination of these. Moreover, increased food demand by rapidly growing populations is another factor contributing to the importance of improving agricultural productivity (Hageback et al., 2005).

The SKY-LUDAS simulation results also demonstrated that farmers in the study area have adapted their land use to the effects of climate change based on income sources and gradual changes in land use for the purpose of making farming systems more resilient and therefore adaptive to climate change impacts. This reflected the complex nature of land-use change and the interaction of behavioural and structural factors associated with the demand, technological capacity, the social relations affecting demand and capacity, and the nature of the environment in question (Verburg et al., 2004). Similar farmer behaviour was reported in the Danangou watershed of China where over the last 20 years farmers have become less dependent on agriculture by adopting more diversified livelihood strategies which makes them less vulnerable to climate variability (Hageback et al., 2005; Yang et al., 2016).

Controversially, it was observed that as the population adapts itself to climate change, the more the population relies on cash crops. Traditional cereal farming are shifted to the cultivation of more valuable crops, farmers have adopted crops that are less resistant to drought such as maize, which is considered in this study as a new crop in the area introduced to cope with increasing climate variability (Amadou, 2015). One justification for this crop diversification strategy could be that local living conditions have changed drastically over the last 20 years, mainly due to economic changes as reported during group discussions. These adaptive responses of farmers were meant to improve their living conditions. Therefore it is difficult to gauge the degree to which increasing climate variability has influenced these decisions (Hageback et al., 2005). Climate change is only one of many factors that will affect global agriculture over the next several decades. The broader impacts of climate change on global markets, hunger, and resource degradation will depend in part on how agriculture meets the demands of a growing population (Reilly and Schimmelpfennig, 1999). This could help link climate change and population dynamics through adaptation and even mitigation, which is a sensitive issue that needs urgent investigation (Stephenson et al., 2010). On the other hand, questions about what climate change factors are mostly likely to raise awareness and motivate changes in agricultural land use are important issues (Bryant et al., 2000). This could then help to discriminate the adding value of improvement in land, labour productivity, greater market-orientation, increased production diversification as well as increased domestic and international competitiveness in agricultural transformation (Quiñones and Diao, 2011; Gautier et al., 2014).

Through the two-step decision-making sub-models, the SKY-LUDAS model was able to simulate the economic impacts of diversification through climate change adaptation options. This is consistent with evidence that the two-stage decision-making routine approach in LB-LUDAS (Villamor, 2012) was an improved method of incorporating decision-making process into the model.

4.2. ABM vs. RPG result comparison

The investigation of the adaptive strategies of local farmers through the development and application of the RPG exercises helped to elucidate the social motivations behind such as: (1) agricultural diversification in the study area, (2) subsistence farming behaviour, (3) primary agricultural land uses, and (4) the cultivation of traditional commercial crops such as rice and groundnut, as well as more recently introduced cash crops like maize and soybeans. Moreover, the use of the RPG revealed that in some communities farmers had shifted from mixed groundnut to monoculture systems and opted for early maturing groundnut variety as a means of coping with increased rainfall variability (Amadou and Villamor, 2015). It was also through the RPG exercises, we learned that some farmers have discontinued cultivating groundnut in mixed-crop systems due to the difficulty of harvesting groundnut during drought or when the rains end early.

The SKY-LUDAS results were compared with the results of Schindler

(2009), who implemented an ABM in the same region and reached the following conclusion: "*A gradual shift among land-use types from traditional cereals farming to cultivation of rice and groundnut was observed during the last decades*." In addition, the results of the RPG exercises conducted in the area show that traditional mixed cereal production systems remained the predominant land-use in the area, whereas crops such as rice and groundnut have greater market value, as do maize and soybean.

Due to the two-step decision-making sub-models the SKY-LUDAS model was able to confirm that rice and groundnut are cash crops used by farmers in the study area as part of their livelihood strategies. Furthermore, the simulation results show that among the different livelihood strategies, groundnut is a cash crop used as a coping measure and therefore a planned adaptation strategy. As a result, this research answers the critical question of whether adaptation practices are stimulated by climate or other factors (Deressa et al., 2008; Gbetibouo, 2009). In fact, when considering the theoretical understanding of principles for investigating adaptation, these authors highlighted some of the major challenges. One major challenge is to isolate climate stimuli response from other stimuli such as market, policy, … that farmers are facing in real world. Secondly, farmers are more concerned with and respond more to short-term climate variability than climate change. And lastly, humans in general can respond in highly variable ways to similar external stimuli.

The findings of RPG exercises helped to understand the trends in subsistence farming and provided greater details about the use of monoculture groundnut systems as agricultural land-use adaptation strategy as simulated by SKY-LUDAS model. This provides additional support for agent-based spatial modelling as a powerful approach to improving understanding of processes of innovation and resource use change (Berger, 2001).

Nevertheless, one of the limitations of SKY-LUDAS is that it is context specific and cannot be transferred easily to other areas. Only the approach through the framework of LUDAS in general could be reused because all the variables and the calibration of the sub-models should be area specific due to the heterogeneity of the decision-making and the ecological processes. Also, another limitation of this work lies on the difficulty of validating results, which is the common problem of most ABM. In general, frequent emergence patterns, strong dynamics in the system and the complex nature are basically challenging in validating such models (Darvishi and Ahmadi, 2014). For this reason, we applied RPG to have some level of convergent validity by comparing the constructs of the two methods (Suphanchaimart et al., 2005; Villamor et al., 2013). Furthermore, the RPGs were applied as its goal is usually to test an hypothesis, or more generally to answer a scientific question (Bousquet et al., 2005; Suphanchaimart et al., 2005; Guyot and Honiden, 2006). Moreover, sensitivity analyses (Schouten, 2013) were not used in this study.

The non-farm activities which can also be substantial in terms of livelihood strategies were also not considered in this study and seen as another limitation.

5. Conclusions

We applied agent-based model for small-scale agriculture in the Upper East Region of Ghana that enables researchers, policy-makers and other stakeholders to explore the effects of alternative scenarios on agricultural land-use adaptation to the effects of climate change variability. The research findings provide greater insight into the interactions between rural communities and local ecosystems. Attempts to identify strategies to mitigate future climate impacts and improve the sustainability of resource use provided a better understanding and ability to anticipate future rural land-use and land-cover change. A key merit of this study was the development and integration of the two-step decision-making sub-models into the decision programme of the LUDAS model, resulting in SKY-LUDAS. This enabled the model to explicitly explore the implications of the awareness of climate change and related weather variability to decisions about adapting agricultural land uses. The results reveal that groundnut farming (especially in monoculture systems) has emerged as another land-use adaptation to climate change for farmers in the study area. This finding was validated by the results of exercise using a RPG that was designed and implemented for that purpose in the study area communities. SKY-LUDAS was able to incorporate the dynamics and interactions as well as process between the social and ecological systems affecting the rural communities in the study area. The model quantified and estimated possible impacts of climate variability on land-use change based on the perception of climate change risks among members of local rural communities. This supports the hypothesis that perception of how particular ecological systems operate determines the approaches that are advocated in attempting to modify or manipulate those ecosystems (Ellis and Swift, 1988). Hence, we believe that this research contributes to resolution of the critical question about whether certain adaptation practices are stimulated by climate related versus other factors.

Acknowledgments

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